U.S. Landfalling and North Atlantic Hurricanes: Statistical Modeling of Their Frequencies and Ratios

Gabriele Villarini[1,2], Gabriel A. Vecchi[3], and James A. Smith[1]

[1] Department of Civil and Environmental Engineering, Princeton University, Princeton, New Jersey

[2] Willis Research Network, London, UK

[3] NOAA/Geophysical Fluid Dynamics Laboratory, Princeton, New Jersey

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Abstract

Time series of US landfalling and North Atlantic hurricane counts and their ratios over the period 1878-2008 are examined and modeled using different climate variables (tropical Atlantic sea surface temperature (SST), tropical mean SST, North Atlantic Oscillation, and Southern Oscillation Index). Two different SST input data (Met Office's HadISSTv1 and NOAA's ERSSTv3b) are employed to examine the uncertainties in the reconstructed SST data on the modeling results. Due to the likely undercount of recorded hurricanes in the earliest part of the record, we consider both the uncorrected hurricane record (HURDAT) maintained by the National Hurricane Center, and a time series with a recently proposed undercount correction.

Modeling of the count data is performed by means of a conditional Poisson regression model, in which the rate of occurrence parameter can be a linear or non-linear function of the climate indices. Model selection is performed following a stepwise approach and using two different penalty criteria. The results of this study do not allow identifying a single "best" model due to the different model configurations resulting from the different SST input data, corrected versus uncorrected count time series, and penalty criteria. These differences were both at the level of the selected covariates and their function relation to the Poisson parameter. Despite the lack of an objectively identified unique final model, we recommend a set of models in which the parameter of the Poisson distribution is a linear function of both tropical Atlantic and tropical mean SSTs.

Modeling of the fractions of North Atlantic hurricanes making landfall in the US is performed by means of the zero-inflated beta regression model. Similar to the count data, it is not possible to identify a single "best" model, but different model configurations are obtained depending on the SST input data, undercount correction, and selected penalty criterion. The results of this study suggest that these fractions are controlled by both local (mostly related to the NAO) and remote (SOI and tropical mean SST) effects.

1 Introduction

North Atlantic hurricanes claim a large toll in terms of fatalities and economic damage every year (e.g., Pielke and Landsea 1998, 1999; Rappaport 2000; Arguez and Elsner 2001; Negri et al. 2005; Ashley and Ashley 2008a; Pielke et al. 2008; Derrig et al. 2008; Saunders and Lea 2005; Ashley and Ashley 2008b; Changnon 2009; Villarini and Smith 2010). Therefore, our improved understanding of the physical mechanisms responsible for their genesis, development, and tracking are not only of interest from a scientific standpoint, but have important societal and economic repercussions as well.

It is currently still unclear what the possible changes in North Atlantic hurricane frequency would be in a warmer climate (e.g., Shepherd and Knutson 2007; Vecchi et al. 2008b; Villarini et al. 2011b; the interested reader is pointed to Knutson et al. (2010) for a recent review), with contradicting results in the sign of these changes, let alone their magnitude (e.g., Bengtsson et al. 1996; Knutson et al. 1998; Emanuel 2005; Mann and Emanuel 2006; Oouchi et al. 2006; Holland and Webster 2007; Bengtsson et al. 2007; Knutson et al. 2008; Gualdi et al. 2008; Emanuel et al. 2008; Sugi et al. 2009; Zhao et al. 2009; Bender et al. 2010). Our capability of predicting future changes in hurricane frequency lays its foundation on our capability to understand and represent the physical processes responsible for the variability exhibited by the existing record at various time scales, from intra- and inter- annual to multidecadal. An important element of this process is examining the dominant factors that explain the variations in frequency of North Atlantic and US landfalling hurricanes.

Several studies have explored the impact of different climate indices on the North Atlantic tropical storm and hurricane frequency. Among the most commonly used indices, we find Atlantic and tropical sea surface temperatures (SSTs), El Niño-Southern Oscillation (ENSO), North Atlantic Oscillation (NAO), West African monsoon, Atlantic Multidecadal Oscillation, Atlantic Meridional Mode (AMM), Madden-Julian Oscillation (MJO), Quasi-Biennal Oscillation (among others, consult Villarini et al. (2010) for a recent list of references). No general agreement still exists regarding which of these climate variables should be included in a model describing North Atlantic and US landfalling hurricane frequencies. For instance, Bove et al. (1998) examined the effects of El Niño on US landfalling hurricanes and found that the probability of two or more US hurricane strikes increased from 28% during an El Niño year to 66% during a La Niña year. Elsner et al. (2001) used a Poisson regression model to examine the relation between US landfalling hurricane data and ENSO and NAO (see also Elsner (2003), Elsner et al. (2004), and Elsner and Jagger (2006) for additional models of US landfalling hurricane counts). Parisi and Lund (2008) found that NAO and the Bivariate El Niño-Southern Oscillation (an index computed from the Southern Oscillation Index and El Niño 3.4) can be used to model the US landfalling hurricane strike count. Dailey et al. (2009) examined the relation between Atlantic SST and US landfalling hurricanes. Vecchi et al. (2011) built a Poisson regression model from 212 years of global atmospheric simulations from the HiRAM-C180 model

(Zhao et al. 2009, 2010) and assumed that both tropical Atlantic and tropical mean sea surface temperature were important predictors, finding that the former exerted a positive impact (increasing frequency of hurricanes with increasing tropical Atlantic SST) and the latter a negative impact (decreasing frequency of hurricanes with increasing tropical mean SST). Kossin et al. (2010) divided the North Atlantic tropical storms and hurricanes into four clusters and investigated their frequency in terms of ENSO, AMM, NAO, and MJO.

Modeling of the North Atlantic hurricanes is complicated by the uncertainties associated with the Hurricane dataset (HURDAT; Jarvinen et al. 1984; Neumann et al. 1993; MacAdie et al. 2009), which is maintained by the National Hurricane Center (NHC). For all the recorded storms starting from 1851, the HURDAT dataset provides information about the latitude, longitude, minimum pressure and maximum wind speed at the center of circulation at the six-hourly scale. The homogeneity of this record has been object of extensive criticisms. Statements about the presence of increasing linear trends are unavoidably affected by the large uncertainties in the record, especially considering the large leverage that the data at the beginning of the time series would exert. There is, therefore, a trade-off between the availability of the longest possible record and having results which are affected by significant uncertainties. To address this issue, several different corrections for possible undercounts have been proposed, each of them based on different assumptions and methodologies (e.g., Landsea et al. 2004; Landsea 2007; Mann et al. 2007; Chang and Guo 2007;

Chenoweth and Divine 2008; Vecchi and Knutson 2008; Landsea et al. 2010; Vecchi and Knutson 2011). In addition, efforts are underway to "reanalyze" the record using historical meteorological observations (e.g., Landsea et al. 2004, 2008). Even though it will never be possible to know with complete certainty the exact number of hurricanes over the entire record, the use of corrections for possible undercounts would mitigate the impact of these errors and allow making more meaningful statements about the results of these study.

In this study we have examined the relation between the climate indices and counts of US landfalling and North Atlantic hurricanes by means of a Poisson regression model. We take the lead from studies already published in the literature (e.g., Elsner and Schmertmann 1993; McDonnell and Holbrook 2004a,b; Elsner et al. 2004; Elsner and Jagger 2004; Sabbatelli and Mann 2007; Elsner et al. 2008; Mestre and Hallegatte 2009; Villarini et al. 2010) and build on them. We consider five different predictors (tropical Atlantic SST, tropical mean SST, NAO averaged over two different periods, and SOI), reflecting our currently understanding of the physical processes responsible for the frequency of North Atlantic hurricanes. In particular, the use of both tropical Atlantic and mean tropical SSTs is partly motivated by the broad evidence in support of the concept that tropical Atlantic SST relative to SST of the global tropics is a more significant predictor for the conditions that impact cyclone frequency than absolute tropical Atlantic SST (e.g., Sobel et al. 2002; Tang and Neelin 2004; Latif et al. 2007; Vecchi and Soden 2007; Swanson 2008; Knutson et al. 2008; Vecchi et al. 2008b; Zhao et al. 2009, 2010; Villarini et al. 2010, 2011b). Rather than assuming a linear relation between covariates and parameter of the Poisson regression model by means of an appropriate link function, we allow for non-linear dependencies as well by means of cubic splines. Moreover, the selection of the most appropriate predictors is performed using two different selection criteria. Villarini et al. (2010) showed that there is not a "single best" statistical model when modeling North Atlantic and US landfalling tropical storms, but different final models result from different selection criteria. To account for likely undercount in the number of North Atlantic hurricanes in the pre-satellite era (pre-1966), we model both the original HURDAT record as well as the HURDAT time series after correcting for undercounts using the approach recently described in Vecchi and Knutson (2011). Finally, we do not restrict ourselves to one single SST dataset, but examine the impact of different SST input data (e.g., Vecchi et al. 2008a; Bunge and Clarke 2009) by employing two different SST records.

As discussed above, modeling the number of hurricanes in the North Atlantic basin and making landfall in the US has been the object of several studies. However, examination of the temporal changes in the fractions of North Atlantic hurricanes making US landfall has received much less attention. Landsea (2007) explored the ratio of landfalling to total tropical storms, and argued that the notable increase over time was evidence for an inhomogeneity of the tropical storm record. Coughlin et al. (2009) examined these ratios, applying different statistical tests. They found that these fractions were different between the first and second half of the 20^{th} century (most likely due to inhomogeneities in the record), but could be considered constant over the most recent part of the record. After applying a correction to the North Atlantic basinwide hurricane record, Vecchi and Knutson (2011) found that the 1878-2008 record of US landfalling hurricane fraction became more stationary. To the best of our knowledge there are no studies attempting to describe the fraction of North Atlantic hurricanes making US landfall in terms of climate variables. Improved understanding of the physical mechanisms responsible for the hurricane landfall would improve our capability of predicting and understanding landfalling hurricanes, with important implications for decision makers and for the insurance and reinsurance industry (e.g., Lonfat et al. 2007). In particular, a model able to describe the fraction of hurricanes making landfall in terms of climate indices could be coupled with predictive models of the overall North Atlantic hurricane activity (e.g., Gray 1984b; Elsner and Jagger 2006; Vitart 2006; Vecchi et al. 2011; consult Camargo et al. (2007) for a review). From a statistical standpoint, modeling of this type of data is complicated by the fact that the ratios are bounded between 0 and 1, with non-zero probability mass at 0 (no hurricanes making landfall). Statistical models able to describe these data revolve around inflated beta distributions and have only recently been presented in the statistical literature (Ospina and Ferrari 2010).

The main questions we address in this study can be summarized as follows:

1. what are the important climate indices to describe the frequency of US landfalling and North Atlantic hurricanes?

2. what are the important covariates to describe the fractions of North Atlantic hurricanes making landfall in the US?

3. what is the sensitivity of these models to hurricane undercounts, SST input data, and criterion for model selection?

The paper is organized in the following way. In Section 2 we describe the data and the climate indices, followed by Section 3 in which we describe the Poisson regression model and the zero-inflated beta regression model used to model the frequency of US landfalling and North Atlantic hurricanes and their ratios. The results of this study are presented in Section 4. Finally, in Section 5 we discuss some of the issues with this study and summarize the main points of this work.

2 Data

2.1 Hurricane Data

The number of North Atlantic hurricanes (Saffir-Simpson Category 1-5) is derived from the HURDAT database (Jarvinen et al. 1984; Neumann et al. 1993; MacAdie et al. 2009), which contains the number of hurricanes since 1851. This dataset, however, is not homogeneous and becomes more prone to missed hurricanes the further back we go. Until 1943, the number of recorded storms relies on ship observations (not homogeneous themselves and affected by changes in the ship tracks; Vecchi and Knutson 2008) and landfall recordings. Organized aircraft reconnaissance flights started in 1944 and complemented the ship accounts. The hurricane record from 1966 is largely based on satellite observations.

These changes in the observation system raised questions about the accuracy of the HURDAT record, in particular regarding the earliest parts (pre-1944). Several different corrections have been proposed to account for likely storm undercounts, each of them based on different hypothesis (e.g., Landsea et al. 2004; Landsea 2007; Chang and Guo 2007; Mann et al. 2007; Vecchi and Knutson 2008; Landsea et al. 2010). These corrections, however, were not specifically developed for hurricanes. Vecchi and Knutson (2011), however, recently proposed a correction for likely undercounts of hurricanes in the North Atlantic basin, following a methodology similar to the one described in Vecchi and Knutson (2008). As far as US landfalling hurricane counts are concerned, we conditionally assume that the record is complete due to the devastating impact that these storms would have had.

In this study we model the yearly number of North Atlantic hurricanes and US landfalling hurricanes over the period 1878-2008. When dealing with the overall North Atlantic hurricane activity, we consider two datasets: time series obtained from the original HURDAT dataset (we will refer to this record as "uncorrected"), and a time series in which the HURDAT dataset is corrected for undercount using the correction in Vecchi and Knutson (2011) (we will refer to this record as "corrected"). These three time series are shown in Figure 1. These data exhibit considerable interannual and interdecadal variability, with periods of higher activity alternating to periods of lower activity. Comparison between the uncorrected and corrected records highlights the largest discrepancies in the earliest parts of the records, in which the undercount correction was larger. These discrepancies become smaller as we move towards the satellite era.

In addition to the modeling of the hurricane counts, we also focus on the statistical modeling of the fraction of the North Atlantic hurricanes that made landfall in the US (Figure 2). These time series are bound between 0 (in a given year, no hurricane made landfall in the US) and 1 (all of the hurricanes formed in the North Atlantic made landfall in the US as hurricanes). While there have been years with no landfalling hurricanes, over 1878-2008 there are no years in which all of the North Atlantic hurricanes made landfall in the US as hurricanes. Once again, we use both the corrected and uncorrected HURDAT database for the overall North Atlantic hurricane activity. Again, there are considerable variations on a variety of timescales with periods of larger US landfalling fraction alternating to periods of lower frequency. When using the uncorrected HURDAT, we observe larger fractions towards the beginning of our record, due to the lower number of recorded North Atlantic hurricanes, similar to Landsea (2007) for tropical storms and Coughlin et al. (2009).

2.2 Climate Indices

We use as possible predictors to describe the frequency of North Atlantic hurricanes, US landfalling hurricanes, and fraction of hurricanes making landfall in the US four different climate indices: tropical Atlantic SST (SST_{Atl}), tropical mean SST (SST_{Trop}), Southern Oscillation Index (SOI), and the North Atlantic Oscillation (NAO). We have focused on these variables because of the availability of relatively high quality data over our study period and for their relation to the physical factors that control the genesis, development and tracking of North Atlantic hurricanes. A warm Atlantic is generally more conducive to increased hurricane activity (e.g., Emanuel 2005; Mann and Emanuel 2006; Vecchi and Soden 2007; Swanson 2008; Zhao et al. 2009; Villarini et al. 2010). Recent studies, however, showed that a better predictor of the North Atlantic tropical storm and hurricane activity is represented by the tropical Atlantic SST relative to the state of the tropics (e.g., Vecchi and Soden 2007; Swanson 2008; Vecchi et al. 2008b; Zhao et al. 2009; Villarini et al. 2010; Vecchi et al. 2011; Villarini et al. 2011b). Hurricane genesis and development is generally suppressed (favored) by increasing (decreasing) vertical shear of the upper level horizontal winds during El Niño (La Niña) events (e.g., Gray 1984a; Wu and Lau 1992; DeMaria 1996). The strength of the trade winds and the position of the Bermuda High are indicated as the physical link between NAO and hurricane activity (e.g., Elsner et al. 2000b, 2001), with effects mostly associated with the steering of the hurricane tracks.

We compute the tropical Atlantic SST anomalies for a box 10N-25N and 80W-20W while the tropical mean SST over a box 30S-30N. Both of them are averaged over the period June-November. We use SST time series obtained from two datasets to examine the sensitivity of our results to different inputs. Similar to Villarini et al. (2010), we use both the UK Met Office's HadISSTv1 (Rayner et al. 2003) and NOAA's Extended Reconstructed SST (ERSSTv3b; Smith et al. 2008). Despite measuring the same quantity (SST), they exhibit differences associated with different methods used to infill missing SST values, as well as different ways of correcting for data inhomogeneities and the use of the satellite record. The SOI time series is averaged over the August-October period and is computed as described in Trenberth (1984). The NAO is computed as in Jones et al. (1997) and averaged over two different periods (May-June (NAO_{MJ}) and August-October (NAO_{AO}); Elsner et al. 2000b, 2001; Elsner 2003; Elsner et al. 2004; Mestre and Hallegatte 2009; Villarini et al. 2010). The selection of these two averaging periods is due to the fact that NAO is stronger during boreal winter and spring (e.g., Hurrell and Van Loon 1997) but we also want to have a period representative of the core of the hurricane season.

3 Statistical Models

3.1 Poisson Regression Model

Poisson regression is a form of Generalized Additive Model (GAM; e.g., Hastie and Tibshirani 1990) in which the predictand is in the form of count data and follows a Poisson distribution. Let us define the number of North Atlantic and US landfalling hurricanes in the i^{th} year by N_i. We can write that N_i follows a conditional Poisson distribution with rate of occurrence Λ_i if:

$$P(N_i = k|\Lambda_i) = \frac{e^{-\Lambda_i}\Lambda_i^k}{k!} \text{ [k = 0, 1, 2, \dots]} \tag{1}$$

The parameter Λ_i can assume the following general formulation:

$$\Lambda_i = \exp[\beta_0 + \beta_1 h_1(z_{1i}) + \beta_2 h_2(z_{2i}) + ... + \beta_n h_n(z_{ni})] \tag{2}$$

where $\{z_{1i}, \dots, z_{ni}\}$ is a vector of n observable covariate random variables for the i^{th} year (see Smith and Karr (1983) and Karr (1991) for a more general formulation). As discussed in the previous section, we consider five predictors (SST_{Atl}, SST_{Trop}, SOI, NAO averaged over two different periods), as well as two-way interactions (e.g., Elsner and Jagger 2004; Mestre and Hallegatte 2009; Villarini et al. 2010).

As a special case of equation 2, we could have that all the beta coefficients are equal to zero, with Λ_i=exp[β_0] (standard Poisson random variable). Moreover, if

$\ln(\Lambda_i)$ linearly depends on the covariates, we have a Generalized Linear Model (GLM; McCullagh and Nelder 1989; Dobson 2001) and we can write that Λ_i=exp$[\beta_0+\beta_1 x_{1i}+\beta_2 x_{2i}+...+\beta_n x_{ni}]$.

In this study, we do not limit the dependence of Λ_i on the covariates (via a logarithmic link function) to be only linear (e.g., Elsner and Schmertmann 1993; Elsner et al. 2000a; Elsner and Jagger 2004, 2006; Sabbatelli and Mann 2007). We also include the case in which the relation between predictand and predictors is by means of a cubic spline (e.g., Mestre and Hallegatte 2009; Villarini et al. 2010). Model selection (in terms of both covariates and their relation to the Poisson parameter) is performed using a stepwise approach, penalizing with respect to both the Akaike Information Criterion (AIC; Akaike 1974) and the Schwarz Bayesian Criterion (SBC; Schwarz 1978). The use of these criteria would help in avoiding model overfit, and represents a trade-off between the complexity and the accuracy of the models. Because of our sample size (131 years), SBC would apply a larger penalty compared to AIC, leading to a more parsimonious model. We, therefore, would expect the model selected according to SBC to be more parsimonious (both in terms of number of covariates and their relation to the rate of occurrence parameter) than the one based on AIC. Villarini et al. (2010) showed how the use of different penalty criteria results in different "best" models for the frequency of North Atlantic and US landfalling tropical storms. Consult the appendix for a discussion about the impact of the correlation among predictors on the selected models.

We evaluate the model performance by analyzing the model residuals, which should be an independent and identically distributed, following a Gaussian distribution (e.g., Rigby and Stasinopoulos 2005). We examine the (normalized randomized quantile) residuals (Dunn and Smyth 1996) by computing the first four moments of their distribution (mean, variance, coefficients of skewness and kurtosis), their Filliben correlation coefficient (Filliben 1975). We also examine quantile-quantile (qq) and worm plots (van Buuren and Fredriks 2001).

All the calculations are performed in `R` (R Development Core Team, 2008) using the freely available `gamlss` package (Stasinopoulos et al., 2007).

3.2 Zero-Inflated Beta Regression

Modeling of the fraction of North Atlantic hurricanes that made lanfall in the US is performed by means of beta regression, which is used to describe rates and proportions (Ferrari and Cribari-Neto 2004). In a beta regression model, the predictand can assume values between 0 and 1 (extremes excluded). The beta distribution does not belong to the exponential family, like the Poisson distribution, and therefore it is outside of the distributions that can be fitted with a GAM or a GLM. Instead, we use the Generalized Linear Model in Location, Scale and Shape (GAMLSS; Rigby and Stasinopoulos 2005; Stasinopoulos and Rigby 2007), which provides a higher degree of flexibility in the selection of the distribution, compared to the classical Generalized Additive Models, Generalized Linear Models, Generalized Linear Mixed Models, or

Generalized Additive Mixed Models. The probability density function (pdf) of the beta distribution can be written as:

$$p(y_i|\alpha,\beta) = \frac{1}{B(\alpha,\beta)} y^{\alpha-1}(1-y)^{\beta-1} \tag{3}$$

where $y \in (0,1)$, α>0 and β>0. We use the GAMLSS reparameterization (Ferrari and Cribari-Neto 2004; Stasinopoulos et al. 2009), in which μ=($\frac{\alpha}{\alpha+\beta}$) and σ=($\frac{1}{\alpha+\beta+1}$) when $\mu \in (0,1)$ and $\sigma \in (0,1)$. The first and second moments of y are μ and $\sigma^2\mu(1-\mu)$, respectively.

The classic two-parameter beta distribution does not include 0 and 1 in the support of the predictand. Our time series, however, has zero values (Figure 2). This shortcoming could be addressed by using the three-parameter zero-inflated beta distribution (Ospina and Ferrari 2010), in which the additional parameter allows y to be equal to zero (it models the probability at zero). The pdf of the zero-inflated beta distribution can be written as:

$$p(y_i) = \nu \tag{4}$$

$$p(y_i|\mu,\sigma) = (1-\nu)\frac{\Gamma(\sigma)}{\Gamma(\mu\sigma)\Gamma[\sigma(1-\mu)]} y^{\mu\sigma}(1-y)^{-1+(1-\mu)\sigma} \tag{5}$$

where equation 4 is valid for y=0 and equation 5 if y∈(0,1). The parameters μ ∈(0,1), σ is strictly positive, and ν ∈(0,1). The expected value of y is equal to $(1-\nu)\mu$ and the variance is equal to $(1-\nu)(\frac{\mu(1-\mu)}{\sigma+1})+\nu(1-\nu)\mu^2$. We use a logit link function for μ and ν, and a logarithmic link function for σ. An even more general version of the beta distribution is the one in which the predictand can assume all the values between 0 and 1, extremes included. We focus on the zero-inflated beta distribution because there are no years in which all of the hurricanes made landfall, and the additional parameter (modeling the probability at y=1) would be equal to zero. The zero-inflated beta distribution is very flexible. It can be symmetric or highly asymmetric depending on the values of the parameters, with a mass of probability at zero (Figure 3; see also Ospina and Ferrari (2010)).

We consider the same five predictors as for the Poisson regression model (SST_{Atl}, SST_{Trop}, SOI, NAO_{MJ}, NAO_{AO}). To the best of our knowledge, studies about the statistical modeling of the fraction of North Atlantic hurricanes making landfall in the US in terms of climate indices are still lacking. Therefore, it is hard to predict what to expect a priori from model selection. Model selection is performed with respect to both AIC and SBC. Diagnostic tools to assess the quality of the fit of the beta inflated distributions are currently object of research (Dr. Ospina, personal communication, 2010). The randomized quantile residuals used for the Poisson regression model do not appear to be applicable because the zero-inflated beta regression model has probability mass at zero, modifying the continuous structure of the residuals. The assessment of the most suitable residual is currently under study, as documented by the three working papers by Dr. Ospina and Dr. Ferrari (Ospina, R., and S.L.P. Ferrari, Inflated beta regression models (Working paper), 2010; Ospina, R., and S.L.P. Ferrari, Some Diagnostic tools for inflated beta regression models (Working paper), 2010; Ospina, R., and S.L.P. Ferrari, A note on bias correction in inflated beta regression models (Working paper), 2010). For these reasons, assessment of the quality of the fit is based on visual comparison between data and the fitted zero inflated beta distribution. More detailed assessment of the quality of the fit should be object of future studies once there is a better understanding on what the most suitable residuals are.

All the calculations are performed in `R` (R Development Core Team, 2008) using the freely available `gamlss` package (Stasinopoulos et al., 2007).

4 Results

4.1 Poisson Regression Model

We start by focusing on the statistical modeling of the number of North Atlantic and US landfalling hurricanes using a Poisson regression model in which the logarithm of the rate of occurrence is a function of SST_{Atl}, SST_{trop}, NAO, and SOI. We consider both linear and smooth (by means of a cubic spline) dependence of the Poisson parameter on these covariates, and include two-way interaction terms. Model selection is performed using a stepwise approach, using both AIC ans SBC as penalty criteria.

We start with the results obtained using AIC as penalty criterion (Figure 4), for the US landfalling hurricanes (top panels), and the uncorrected (middle panels) and corrected (bottom panels) North Atlantic hurricane counts. The results for both of the SST datasets are shown (HadISSTv1: left panels; ERSSTv3b: right panels). We summarize the parameter estimates and the model fit performance in Figure 5 and Table 1. In modeling the landfalling hurricanes (Figure 4, top panel), different covariates and functional relations between predictors and the rate of occurrence parameter are identified depending on the SST input data. When using the HadISST data, NAO_{MJ}, SST_{Atl}, and SST_{trop} are significant predictors. There is a linear relation between NAO_{MJ} and the logarithm of the rate of occurrence parameter, while the relation between SST_{Atl} and SST_{trop} and $\ln(\Lambda)$ is by means of a cubic spline. When using ERSST data, SOI is added as a significant predictor. In this case, there is a linear relation between SST_{trop} and SOI and $\ln(\Lambda)$. The number of degrees of freedom for the fit is larger when using HadISST (10) than ERSST (8) due to the use of cubic splines for tropical Atlantic and tropical mean SSTs. Similar to what found for US landfalling tropical storms (Villarini et al. 2010), tropical Atlantic and tropical mean SSTs are always important predictors. Moreover, the coefficient of SST_{Atl} and SST_{trop} have opposite signs, pointing to relative SST as an important factor in describing US landfalling hurricane frequency. Despite the complex patterns exhibited by the hurricane record, these models are able to describe its behavior. Assessment of the quality of the fit (Figure 5 and Table 1) does not highlight any significant problem with these models.

The time series of hurricane counts for the entire North Atlantic basin exhibit more marked multidecadal variations than observed in the US landfalling hurricane count time series (Figure 4, middle and bottom panels). When modeling the uncorrected data and using the HadISST data, SOI, tropical Atlantic and tropical mean SSTs are retained as important predictors. The relation between SOI and the rate of occurrence parameter is linear, while Λ is related to SST_{Atl} and SST_{trop} by means of a cubic spline (via a logarithmic link function). The results obtained using the ERSST input data are slightly different. Even in this case, both tropical Atlantic and tropical mean SSTs are retained as important predictors and, once again, they have opposite sign. However, their relation to the logarithm of the Poisson parameter is now linear. While SOI is included in the final model, NAO_{AO} is also included. Because the relation between tropical Atlantic and mean tropical SSTs and $\ln(\Lambda)$ is linear when using ERSST, the number of degrees of freedom used for the fit is smaller (5 against 10). These models are able to well reproduce the behavior exhibited by the data, with decades of increased hurricane activity alternating to decades of lower activity. The fit diagnostics do not indicate any large problem with these models (Figure 5 and Table 1).

Similar to what was found for the uncorrected dataset, the models for the corrected time series always include tropical Atlantic and mean tropical SSTs as important predictors. In agreement with the idea that tropical Atlantic SST relative to the tropical mean SST is more important than tropical Atlantic SST alone, the coefficients of SST_{Atl} and SST_{trop} have opposite signs (positive for the former and negative for the latter). These statements are valid independently of the SST data used. When using HadISST data, NAO is retained as an important predictor. The relation between $\ln(\Lambda)$ and NAO is linear, while is by means of a cubic spline for tropical Atlantic and tropical mean SSTs. If we use ERSST data, the results (in terms of covariates and their relation to Λ) are similar to what found for the uncorrected dataset. The logarithm of the rate of occurrence is linearly related to SOI, NAO_{AO}, SST_{Atl} and SST_{trop} (the number of degrees of freedom used for the fit are less than what found using the HadISST data due to the linear dependence). These models are able to well reproduce the behavior exhibited by the data, with the alternation of periods of increased and decreased frequencies. The diagnostic measures used to assess the quality of the fit tend to support the modeling results.

So far we have been performing model selection using AIC as penalty criterion. Similar to Villarini et al. (2010), we also use SBC as penalty criterion, expecting that these models would be more parsimonious in terms of both number of covariates and their relation to the rate of occurrence parameter (i.e., a smaller number of degrees of freedom used for the fit). We summarize the model results in Figures 6 and 7 and Table 2. When modeling the US landfalling hurricane counts and using HadISST data, we find that the same covariates we found for AIC are retained as important (NAO, SST_{Atl} and SST_{trop}). However, where the models based on AIC and SBC differ is in their relation to the rate of occurrence parameter. In this case, these three covariates are linearly related to $\ln(\Lambda)$, and four degrees of freedom are used for the fit. The results obtained using ERSSST suggest that SOI and tropical Atlantic and tropical mean SSTs are important predictors to describe the frequency of US landfalling hurricanes. Once again, this is more parsimonious than the corresponding model based on AIC (four versus eight degrees of freedom used for the fit). These models are able to reproduce the behaviors exhibited by the data, and the fit diagnostics do not suggest any significant problem with these fits (Figure 7 and Table 2). Based on all these models, tropical Atlantic and mean tropical SSTs are always important predictors and their coefficients have opposite sign. These statements are valid independently of the input SST data and penalty criterion. The same is not true for NAO and SOI, because their inclusion in the final model depends on the selected penalty criterion and/or SST input data. These findings add supporting evidence to the key role of relative SST (tropical Atlantic minus tropical mean SSTs) in the frequency of US landfalling hurricanes and tropical storms (see also Villarini et al. (2010)).

The model for the uncorrected time series using SBC as penalty criterion includes different covariates with respect to what we found when using AIC. The only two covariates retained as important in the final model are SOI and tropical Atlantic SST, independently of the SST dataset. Both of them are linearly related to the rate of occurrence parameter via a logarithmic link function, resulting in only three degrees of freedom used for the fit. This is different from what we found using AIC as penalty criterion, since tropical mean SST was always retained as an important predictor. The model based on ERSST has a smaller AIC and SBC value than the one based on HadISST (Table 2), suggesting that using ERSST results in a better agreement to the data than using HadISST. These models are able to capture the variability exhibited by the data, and the fit diagnostics do not indicate any problem with these models (Figure 7 and Table 2).

When modeling the corrected time series, we find that, independently on the SST input data, the only two predictors retained as important are tropical Atlantic and mean tropical SSTs. These covariates are linearly related to the logarithm of the rate of occurrence parameter. Despite being parsimonious (only three degrees of freedom are used for the fit), these models are able to well reproduce the variability exhibited by the data. Assessment of the model fit (Figure 7 and Table 2) does not indicate any significant problem with these models. The coefficients of these two covariates have opposite sign, with the absolute value of the coefficient of SST_{trop} being slightly larger than the one for SST_{Atl}. The values of these coefficients are in agreement with what found by Vecchi et al. (2011) (1.707 for the intercept, +1.388 for tropical Atlantic SST, and -1.521 for tropical mean SST), who built a Poisson regression model from 212 years of model runs from the HiRAM-C180 model (Zhao et al. 2009, 2010). These results indicate that both tropical Atlantic and mean tropical SSTs are necessary to describe the temporal evolution of the North Atlantic hurricane counts. Moreover, a uniform increase in SST would result in a slight decrease in North Atlantic hurricane counts because the coefficient for SST_{trop} is slightly larger in absolute value than the one for SST_{Atl}. These results are in agreement with findings for the North Atlantic tropical storm frequencies (Villarini et al. 2010, 2011b).

All of these modeling results provide information about the sensitivity of the model selection to the selected penalty criterion and SST input data. Villarini et al. (2010) came to the similar conclusions when modeling the US landfalling and North Atlantic tropical storm count time series. Among the different models, they also suggested using a parsimonious model in which the logarithm of the rate of occurrence depends linearly on tropical Atlantic and tropical mean SSTs. This simple model was then used by Villarini et al. (2011b) to examine possible changes in US landfalling and North Atlantic tropical storm frequency under different climate change scenarios and using 24 climate models. In this study, this parsimonious model was selected as the final model for the corrected hurricane count time series when penalizing with respect to SBC. For sake of completeness, we include the results obtained by modeling the US landfalling (Figure 8) and uncorrected (Figure 9) hurricane count time series with a Poisson regression model in which the logarithm of the rate of occurrence parameter is a linear function of both tropical Atlantic and mean tropical SSTs. The models for the US landfalling hurricanes is able to reproduce the variability exhibited by the data, with no significant issues highlighted by the fit diagnostics. The values of the AIC are larger than what we found for the previous models, while the SBC values are close to those obtained by penalizing with respect to SBC and smaller than those obtained by penalizing with respect to AIC. When dealing with the uncorrected data, a model based on only tropical Atlantic and tropical mean SSTs is able to describe the variability exhibited by the data reasonably well (Figure 9). The results concerning the quality of the fit do not point to any significant problem with these models. The values of AIC and SBC for these models are consistently larger than those obtained by the stepwise approach.

Similar to what found in Villarini et al. (2010), there is not a unique "best" model, but different final models are obtained depending on the penalty criterion and the SST input data. In general, we would suggest describing as linear the relation between covariates and the logarithm of the rate of occurrence parameter in agreement with the parsimony principle and because at this point there are no clear physical or statistical reasons indicating that this functional dependence should be of a more complicated form. When modeling the US landfalling hurricane counts, the only covariates that are always included as important for any model configuration are tropical Atlantic and tropical mean SSTs. We, therefore, suggest using this parsimonious model. However, NAO_{MJ} is often included in the final models and it would be reasonable to include it as well in a slightly less parsimonious model.

It is harder to come up with recommendations for the "best" model for the uncorrected dataset. In this case, only SOI and tropical Atlantic SST are always included in the final models, while tropical SST is an important predictor only when performing model selection using AIC as penalty criterion. We would have expected SST_{trop}

to be included as well, based on other studies on the sensitivity of tropical storms and hurricanes in dynamical models (e.g., Knutson et al. 2008; Zhao et al. 2009, 2010; Villarini et al. 2010; Vecchi et al. 2011; Villarini et al. 2011b). Rather than a real "climate" feature, these results are likely due to the large impact of hurricane undercounts. For this reason, we recommend not using the original (uncorrected) HURDAT data without accounting for the undercount correction.

The results from the modeling of the corrected dataset are more consistent with our current understanding of the physical processes at play in the genesis and development of North Atlantic hurricanes. Tropical Atlantic and tropical mean SSTs are always retained as important predictors, independently of the penalty criterion and SST input dataset. When penalizing with respect to AIC, NAO is also included. However, when using SBC as penalty criterion, only the two SST predictors are retained (when using both HadISST and ERSST data). To describe the frequency of North Atlantic hurricanes, we therefore recommend a parsimonious model in which the logarithm of the rate of occurrence parameter is a linear function of both SST_{Atl} and SST_{trop}.

4.2 Zero-Inflated Beta Regression Model

We model the fraction of hurricanes making landfall in the US using a zero-inflated beta regression model. We consider both uncorrected and corrected time series, five covariates, two SST datasets, and two penalty criteria. In Figure 10 we show the results obtained when using AIC as penalty criterion for model selection. We summarize the values of the parameters of these models in Table 3. When we consider the fractions based on the uncorrected dataset, we observe a consistent picture in terms of covariates, independently of the SST input data. The parameter μ is a linear function of NAO_{MJ} and tropical mean SST via a logit link function. The parameter σ is a linear function of NAO_{AO} by means of a logarithmic link function. Finally, the parameter ν depends linearly on SOI using a logit link function. These models are able to describe the complex behavior exhibited by the data. In particular, up to the 1940s there is a tendency towards higher ratios compared to the more recent period. This behavior could be explained by considering the likely undercount of hurricanes in the pre-satellite era. Based on the covariates retained as important predictors during the model selection, we observe both local (NAO) and remote (SOI and tropical mean SST) effects are important in describing these fractions. Both of these influences control the average ratio for a given year, because the expected value of the zero-inflated beta distribution depends on both μ and ν. We would have expected NAO to be a significant covariate because of its possible link to storm steering (e.g., Elsner et al. 2000b, 2001). We have that the sign of the coefficients for NAO is always negative, indicating that a small value of this index would correspond to a more negative NAO phase, with the Bermuda High moving more towards the eastern Atlantic, and an increased mean value (keeping everything else constant). The fact that SOI is an important predictor in describing the probability of US landfalling hurricanes was also discussed in Bove et al. (1998).

When we consider the fractions based on the corrected dataset, we see some similarities but also some differences with the results obtained using the uncorrected dataset. The parameter μ is a linear function of both NAO covariates (averaged over both May-June and August-October) and tropical mean SST (by means of a logit function). SOI is the only predictor retained as important for ν. These results are common to both SST input datasets. The only difference in terms of covariates between the model in which we use HadISST or ERSST data is for σ: when we use HadISST data, this parameter is a function of only NAO_{MJ}, while if we use ERSST data, it is a function of both NAO_{AO} and tropical Atlantic SST. Using the corrected record, we no longer have a more marked increased in the fraction of landfalling hurricanes in the earlier part of the record because of the undercount correction. Both of the NAO covariates (averaged over both May-June and August-October) are included. SOI is the covariate that controls the probability mass at zero. Depending on whether we use HadISST or ERSST data, tropical Atlantic SST is included as a significant covariate for the parameter σ. There is still year-to-year variability, but the multidecadal variability exhibited by the hurricane frequency (Figure 1) is no longer clearly visible (see also Coughlin et al. (2009)).

We have performed model selection using SBC as penalty criterion as well. For both of the hurricane and SST datasets, the final models are the ones with constant parameters. It is worth recalling that assessment of the quality of the fit is based on visual comparison between model results and observations. We did not perform a more quantitative and thorough analysis of the residuals, since the selection of the most suitable residuals for the zero-inflated beta distribution is currently object of separate studies in the statistical literature.

5 Conclusions

We have performed statistical modeling of the North Atlantic and US landfalling hurricane counts and the fraction of hurricanes making landfall into the US over the period 1878-2008. The main findings of our study can be summarized as follows:

1. We considered two different hurricane datasets (original HURDAT and accounting for likely undercount with the correction described in Vecchi and Knutson (2011)), five different covariates (NAO averaged over the period May-June and August-October, SOI, tropical Atlantic SST and tropical mean SST), and two different SST datasets (HadISSTv1 and ERSSTv3b). Selection of important covariates was performed by following a stepwise approach and using AIC and SBC as penalty criteria. Modeling of the count data is performed by means of a Poisson regression model, while modeling of the fraction of storms making landfall in the US by means of the zero-inflated beta regression model.

2. Depending on the penalty criterion and SST input data, we obtained different final models. These results indicate that there is not a unique "best" model from

a statistical standpoint. The results of the statistical modeling effort should help in assessing what the important predictors are. However, the statistical analyses should be complemented by physical reasonings.

3. When modeling US landfalling and North Atlantic hurricane counts with the undercount correction by Vecchi and Knutson (2011), tropical Atlantic and tropical mean SSTs are always retained as important predictors in the final models, independently of the penalty criterion and SST data. The coefficients of these two predictors tend to have similar magnitude but opposite sign. Their values are very similar to those in Vecchi et al. (2011), who estimated them not from the observations but from 212 years of model runs from the HiRAM-C180 model across a broad range of climates. These results provide supporting evidence to the importance of relative rather than absolute Atlantic SST in describing the frequency of US landfalling and North Atlantic tropical storms and hurricanes.

4. We used a zero-inflated beta regression model to describe the fraction of North Atlantic tropical storms making landfall in the US in terms of climate indices. We found that the observations are influenced by both local and remote effects. In particular, the local effects are mostly related to the NAO, which is always selected as an important covariate to describe the magnitude and variability of these fractions. On the other hand, remote effects are associated with tropical mean SST and SOI, with the former selected as an important predictor for the

parameter μ, and the latter as the only covariate that appears to be useful in describing the probability of having no tropical storms making landfall.

Despite the promising results, the zero-inflated beta regression model has been the object of studies in the statistical literature only recently (Ospina and Ferrari 2010). Assessment of the quality of the fit was performed only at the qualitative level, by comparing the observed fractions to the modeled results. Studies examining the most suitable residuals as diagnostic tools are currently under way (Dr. Ospina, personal communication, 2010). Moreover, model selection using SBC as penalty criterion does not identity any of the climate indices as significant predictors. It is possible that covariates different from those employed in this work could provide more stable results.

5. Different studies investigated landfalling hurricanes by dividing the US into subregions (e.g., Gulf of Mexico, East Coast, Florida Panhandle; e.g., Dailey et al. 2009; Brettschneider 2008; Smith et al. 2007; Nakamura et al. 2009; Kossin et al. 2010). Future studies examining the fractions of hurricanes making landfall in specific US sub-areas could help highlighting clearer features that may have been disguised when focusing on the entire North Atlantic basin and US coastline.

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7 Appendix: Impact of Collinearity

To describe the relation between North Atlantic and US landfalling hurricane frequencies and climate indices we have used NAO, SOI, SST_{Atl}, and SST_{trop} as predictors. Model selection was performed by means of a stepwise approach using AIC and SBC as penalty criteria. We have found that both tropical Atlantic and tropical mean SSTs are always retained as important predictors for US landfalling and corrected data (for the uncorrected dataset, tropical mean SST is not included when penalizing with respect to SBC). This statement is valid independently of the selected penalty criterion and SST input data. One element that requires further discussion is the fact that tropical Atlantic and tropical mean SSTs are positively correlated (the value of the correlation coefficient between these two covariates is equal to 0.73 for HadISSTv1 and 0.78 for ERSSTv3b data), possibly affecting the outcome of our modeling efforts. Even though these values of correlation may seem large, they are smaller than what found in other studies in which model selection was performed with respect to these penalty criteria (e.g., Burnham and Anderson 2004; Stasinopoulos and Rigby 2007). On this matter, Burnham and Anderson (2002) suggest not to drop a predictor unless the correlation coefficient is extremely high (near collinearity problem). They indicate $|0.95|$ as a cutoff value for dropping a covariate. Nonetheless, to show that relative SST (tropical Atlantic SST minus tropical mean SST; SST_{rel}) is a key factor in explaining the frequency of North Atlantic and US landfalling hurricanes, we use the variance inflation factor (VIF), a diagnostic tool routinely used to assess the impact of collinearity.

The VIF allows quantifying the “inflation” of the sampling variance of an estimate coefficient due to collinearity. We compute the VIF using the `vif` function in the `Design` package (Harrell Jr 2009) in `R` (R Development Core Team 2008), in which the methodology presented in Davis et al. (1986) is implemented (consult Wax (1992)). A VIF value of 1 indicates that the predictors are uncorrelated, while larger values reflect increasing degrees of correlation among covariates.

In order to evaluate whether collinearity could have an unacceptably high impact on the modeling results, different rules of thumb has been proposed, and a VIF cut-off value of 10 is generally adopted (e.g., O’Brien 2007). Davis et al. (1986) refer to a VIF value larger than 10 as “indicating a modest amount of dependency among the variables.” In this study, we set a VIF value of 10 to decide whether collinearity represents a substantial problem.

Let us start with US landfalling hurricanes. If we use all the five predictors and the HadISST data, the largest value of VIF we obtain is 2.81. This value slightly increases when we use the ERSST data (VIF equal to 2.87), reflecting the larger correlation between tropical Atlantic and tropical mean SSTs for this dataset. For the final models obtained using AIC and SBC as penalty criteria and both of the SST data, the results are similar, with the largest value of VIF equal to 2.87. When dealing with the uncorrected and corrected records, we come to the same conclusion, independently of the model configuration and SST input data. The largest VIF value for the uncorrected data is 2.95, while it is equal to 2.87 for the corrected record. Based on these results (VIF much smaller than 10), we can conclude that the dependence among predictors does not have a significant effect on the outcome of this study (see also discussion in Villarini et al. (2011a)).

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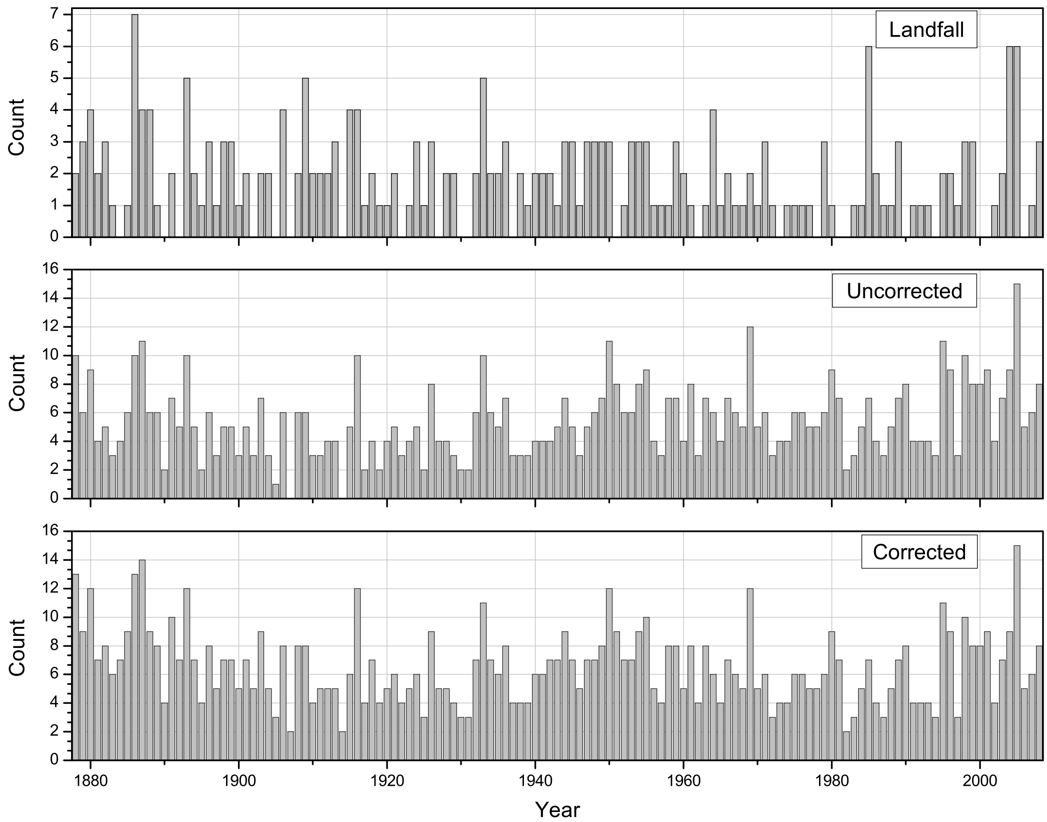


Figure 1: Time series of the count of US landfalling hurricane (top panel) and of the North Atlantic hurricanes using the original HURDAT dataset (middle panel) and after applying the correction in Vecchi and Knutson (2011) (bottom panel).

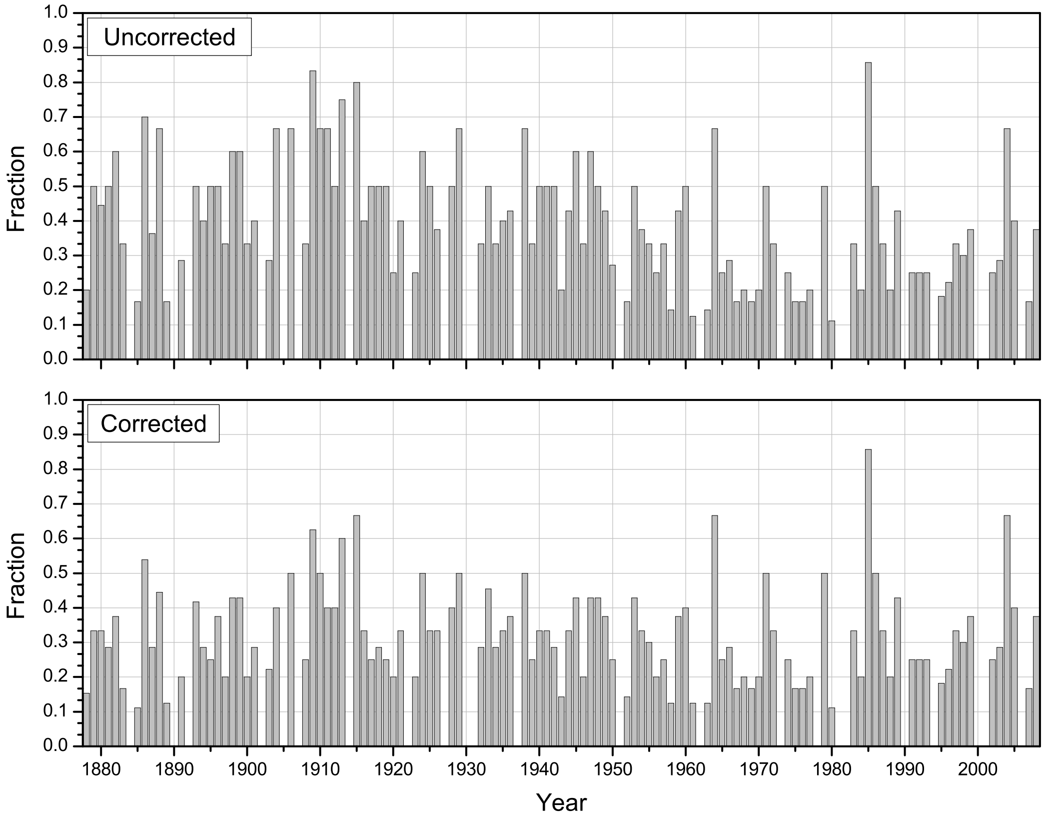
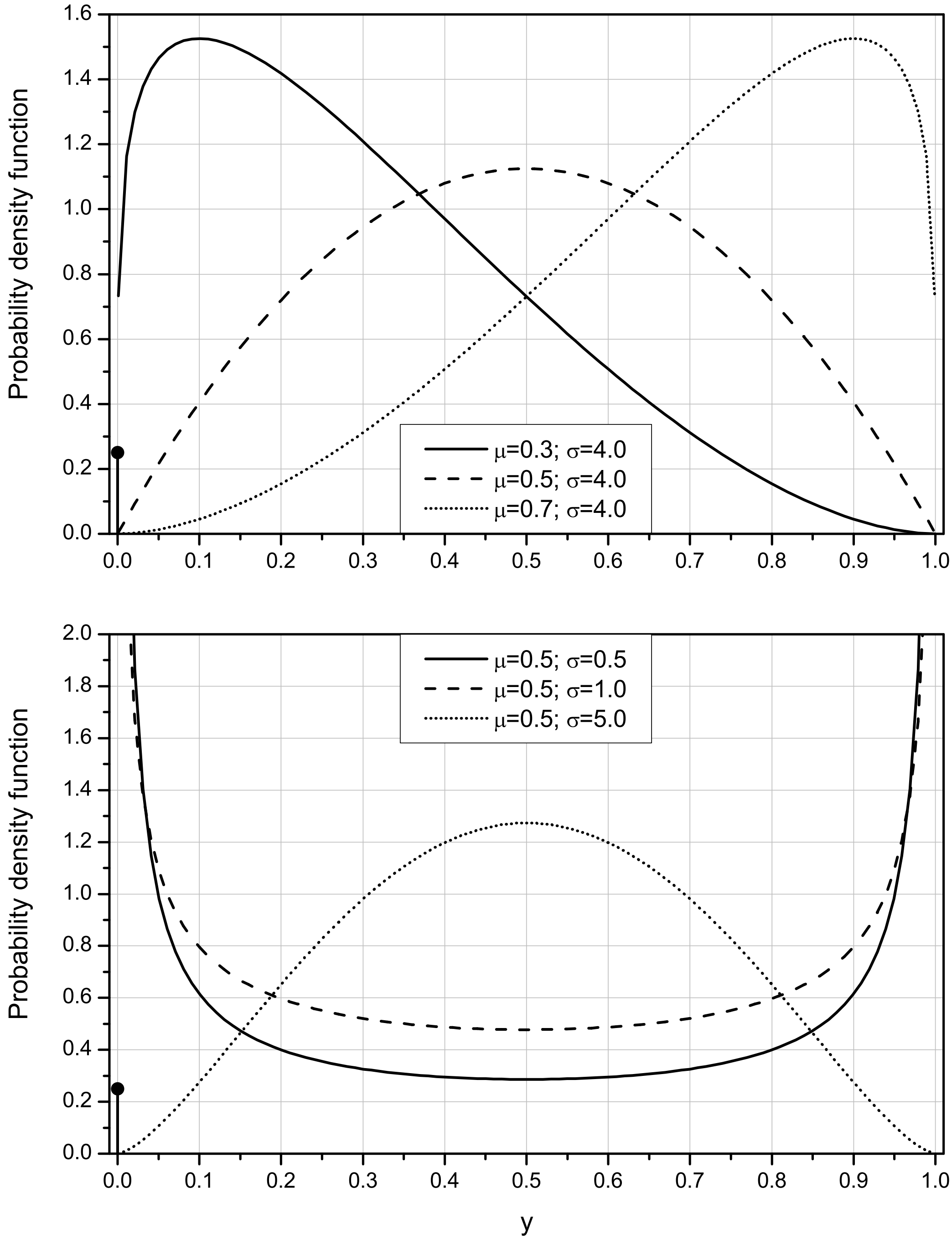


Figure 2: Time series of the fraction of the North Atlantic hurricanes that made landfall in the US, using the original HURDAT database (top panel), and after correcting it as in Vecchi and Knutson (2011) (bottom panel).



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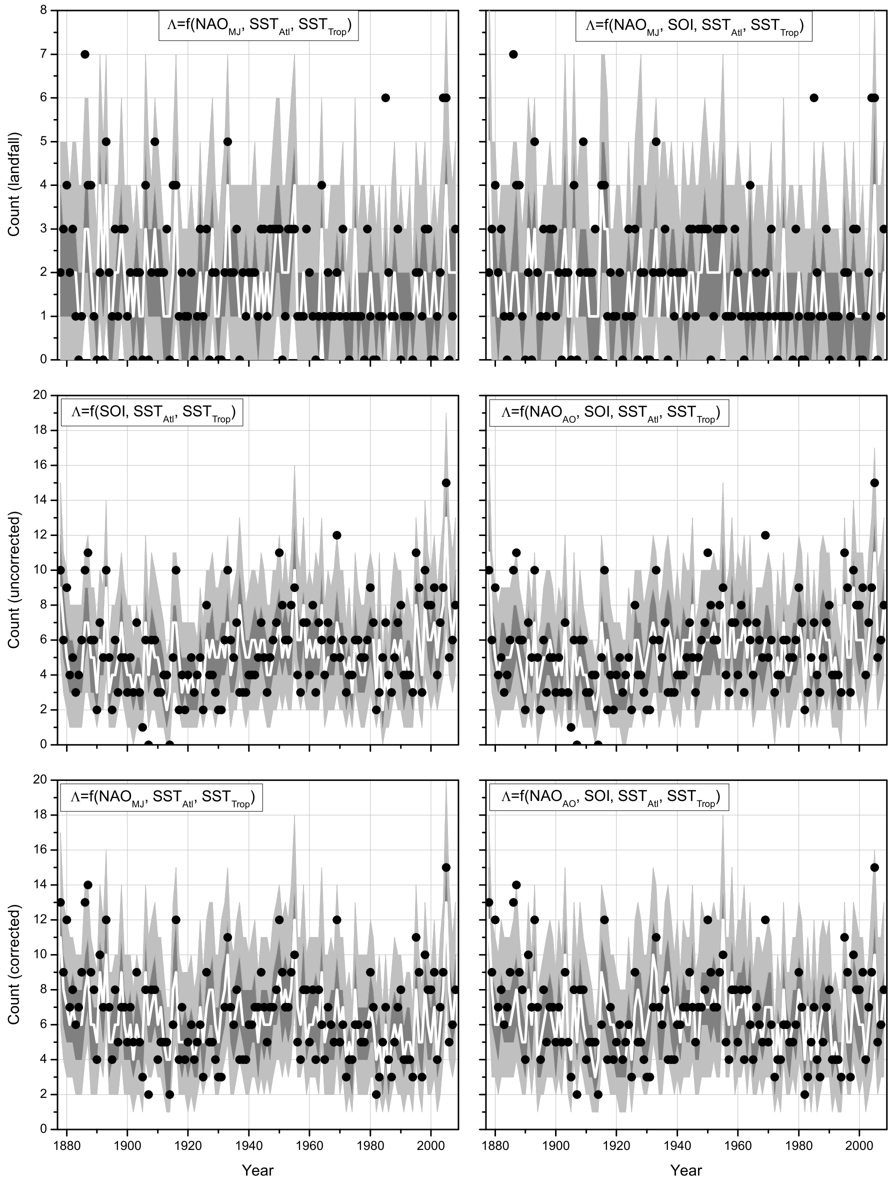

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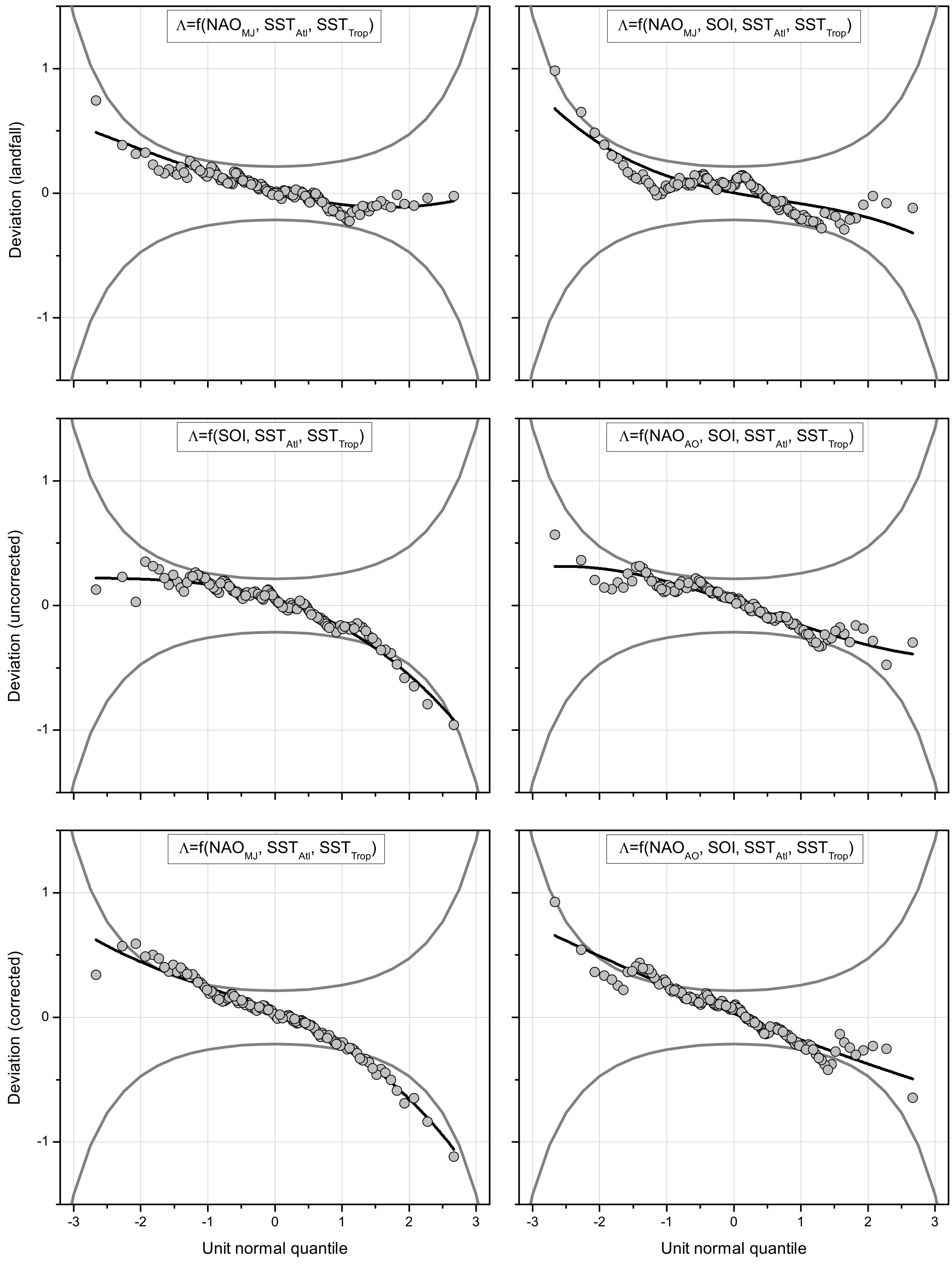

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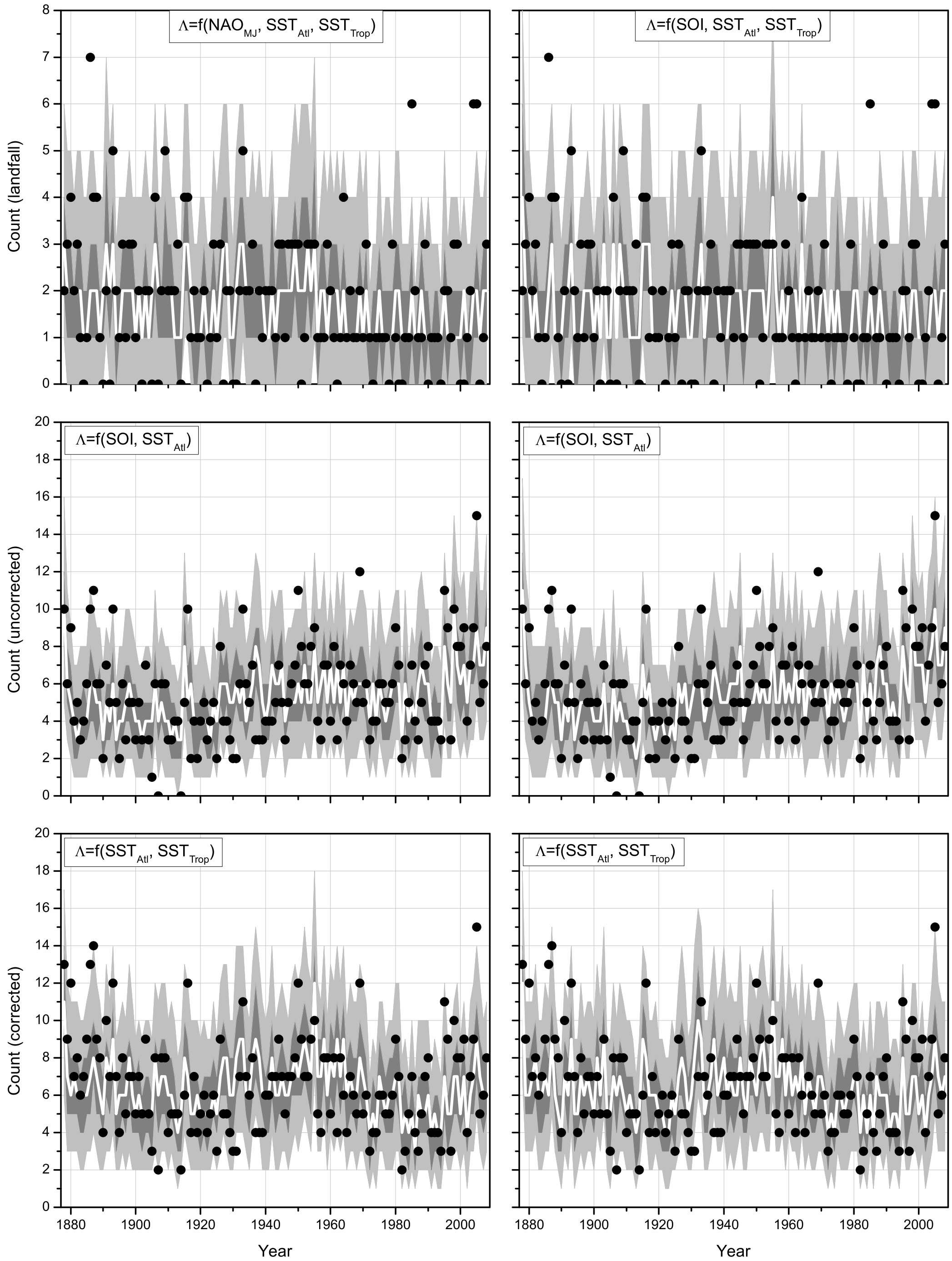

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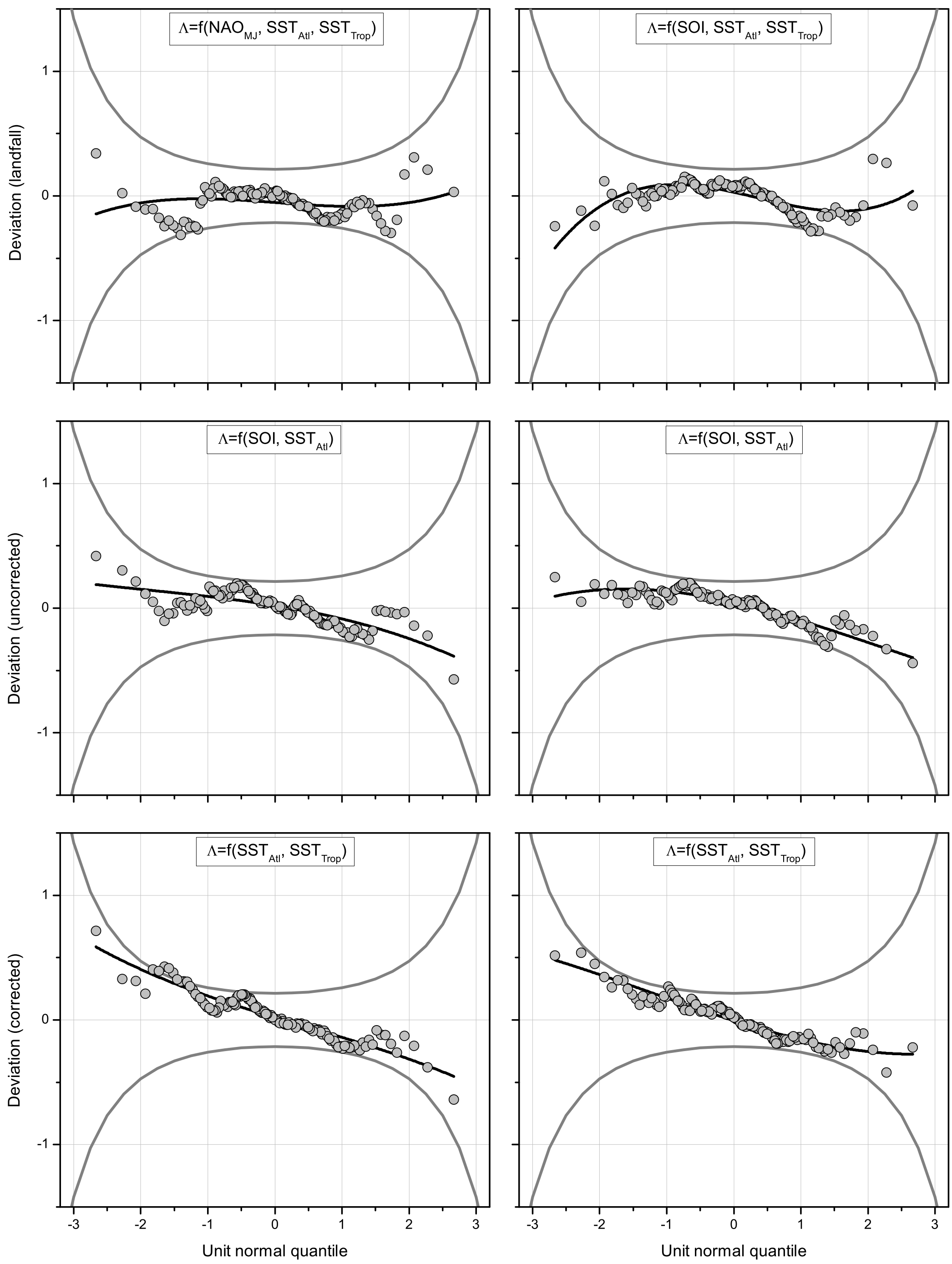

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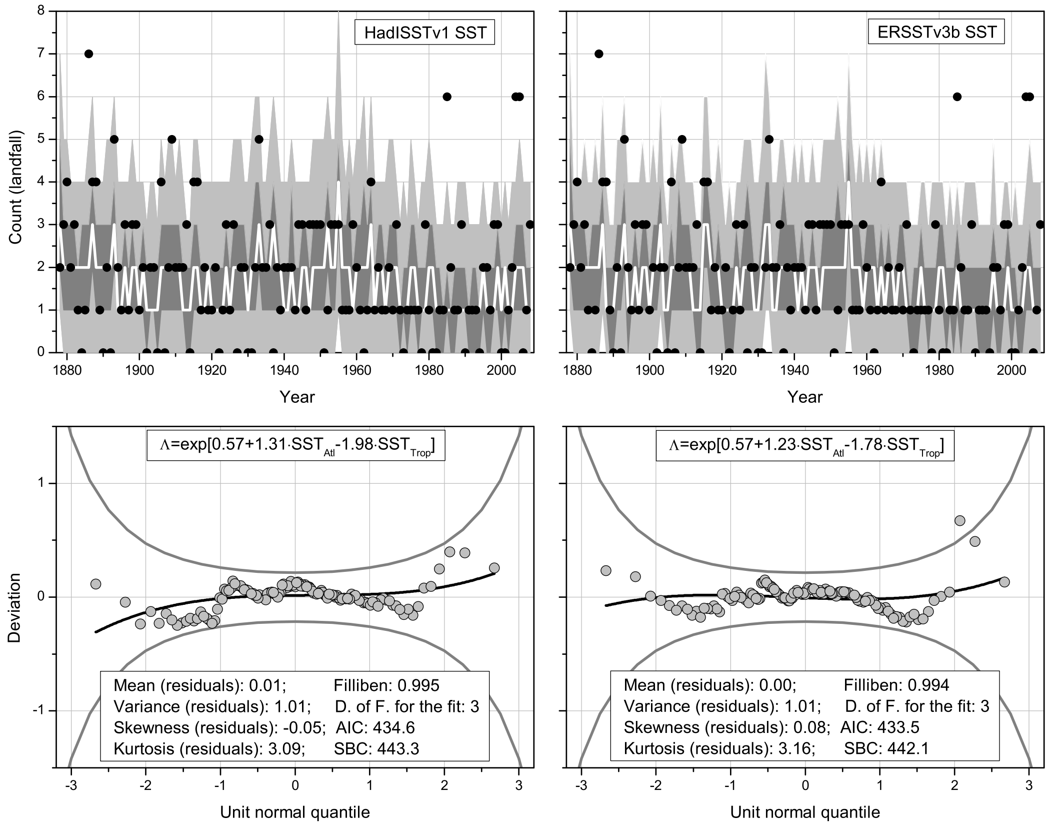

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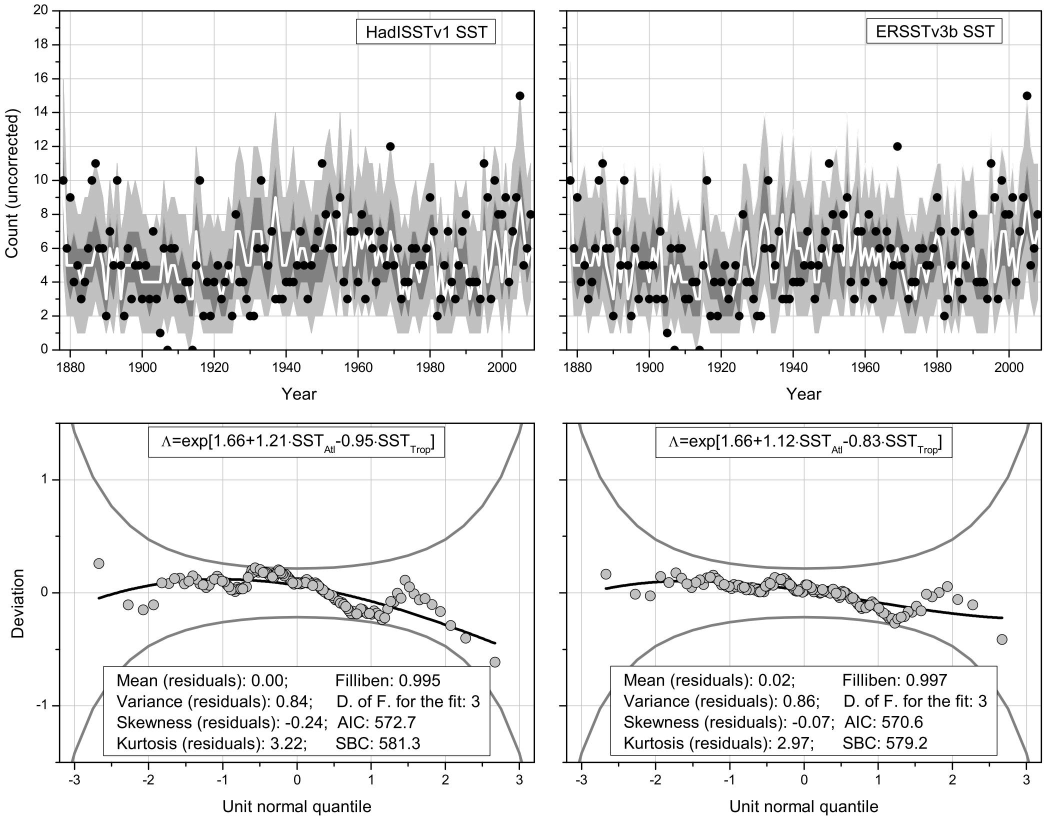

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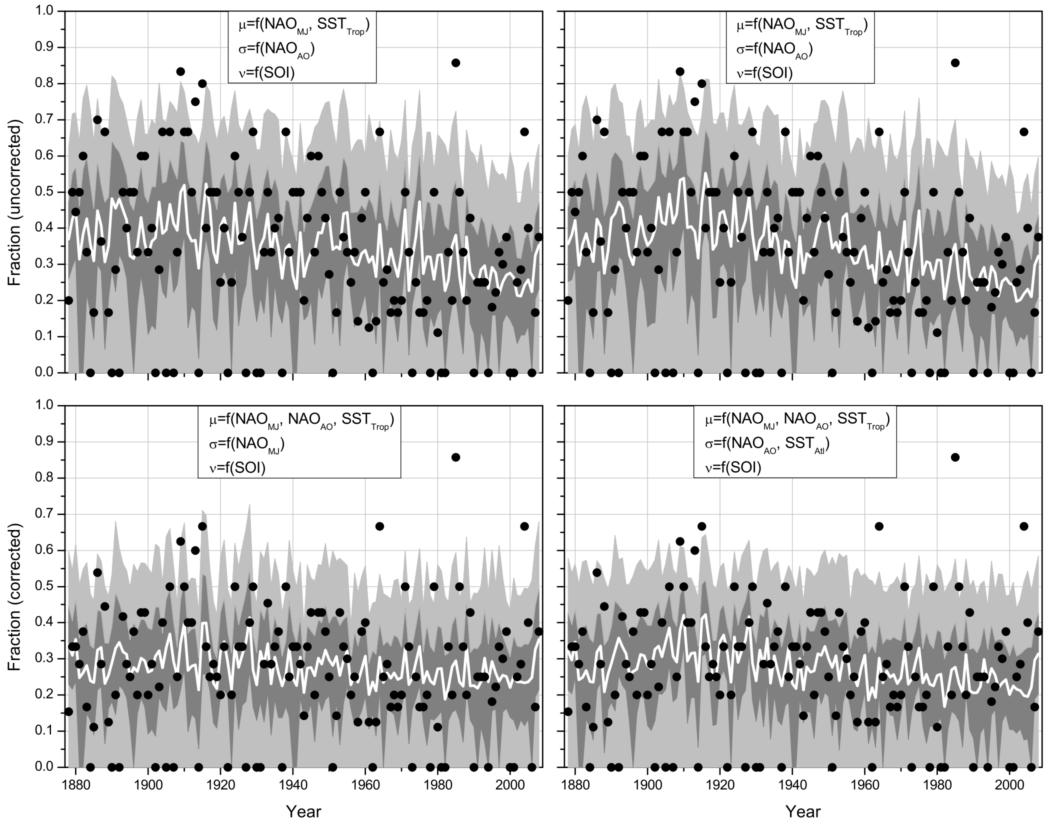

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Table 1: Summary statistics for the Poisson modeling of hurricane counts using climate indices as covariate. Model selection is performed with respect to AIC. The first value is the point estimate, while the one in bracket is the standard error; "D. of F. for the fit" indicates the degrees of freedom used for the fit. In each cell, the values in the first (second) row refer to the model using the HadISSTv1 (ERSSTv3b). When "cs" is present, it means that the dependence of Λ_i on that covariate is by means of a cubic spline (otherwise, linear dependence is implied).

	Landfall	Uncorrected	Corrected
Intercept	0.50 (0.07) 0.52 (0.07)	1.67 (0.04) 1.68 (0.04)	1.84 (0.04) 1.86 (0.04)
NAO_{MJ}	-0.18 (0.07) -0.14 (0.07)	- -	-0.06 (0.03) -
NAO_{AO}	- -	- 0.07 (0.04)	- 0.07 (0.04)
SOI	- 0.09 (0.04)	0.05 (0.03) 0.09 (0.03)	- 0.05 (0.02)
SST_{Atl}	1.21 (0.34; cs) 0.94 (0.31; cs)	1.15 (0.20; cs) 1.03 (0.18)	1.12 (0.18; cs) 1.01 (0.17)
SST_{Trop}	-1.93 (0.49; cs) -1.32 (0.44; cs)	-0.75 (0.30; cs) -0.51 (0.25)	-1.37 (0.25; cs) -0.97 (0.23)
D. of. F. for the fit	10 8	10 5	10 5
Mean (residuals)	0.04 0.03	-0.00 0.02	0.01 0.04
Variance (residuals)	0.78 0.76	0.67 0.70	0.55 0.62
Skewness (residuals)	0.18 0.13	-0.36 -0.06	-0.25 -0.05
Kurtosis (residuals)	2.99 2.77	2.92 3.00	2.72 2.92
Filliben (residuals)	0.997 0.993	0.994 0.997	0.996 0.997
AIC	423.6 425.9	559.9 560.4	571.8 573.2
SBC	452.3 448.9	588.6 574.8	600.5 587.6

Table 2: Same as Table 1, but using SBC as penalty criterion.

	Landfall	Uncorrected	Corrected
Intercept	0.49 (0.08) 0.57 (0.07)	1.68 (0.04) 1.68 (0.04)	1.86 (0.03) 1.85 (0.04)
NAO_{MJ}	-0.18 (0.07) -	- -	- -
NAO_{AO}	- -	- -	- -
SOI	- 0.11 (0.04)	0.10 (0.02) 0.11 (0.02)	- -
SST_{Atl}	1.18 (0.34) 1.07 (0.30)	0.73 (0.13) 0.68 (0.11)	1.11 (0.17) 1.05 (0.16)
SST_{Trop}	-1.95 (0.49) -1.41 (0.44)	- -	-1.33 (0.25) -1.17 (0.22)
D. of. F. for the fit	4 4	3 3	3 3
Mean (residuals)	-0.05 -0.00	0.00 0.02	0.03 0.01
Variance (residuals)	0.99 0.94	0.82 0.79	0.68 0.71
Skewness (residuals)	-0.01 -0.17	-0.10 -0.17	0.04 0.10
Kurtosis (residuals)	3.11 3.42	2.84 2.93	2.79 2.94
Filliben (residuals)	0.993 0.994	0.995 0.997	0.997 0.998
AIC	429.5 429.7	568.7 563.6	578.6 577.1
SBC	441.0 441.2	577.3 572.2	587.3 585.7

Table 3: Summary statistics for the zero-inflated beta regression modeling of the fraction of hurricanes making landfall using climate indices as covariate. Model selection is performed with respect to AIC. The first value is the point estimate, while the one in bracket is the standard error. In each cell, the values in the first (second) row refer to the model using the HadISSTv1 (ERSSTv3b). The dependence between predictors and parameters is linear (via an appropriate link function).

Uncorrected	μ	σ	ν
Intercept	-0.45 (0.07) -0.46 (0.07)	2.11 (0.13) 2.14 (0.13)	-1.65 (0.25) -1.65 (0.25)
NAO_{MJ}	-0.14 (0.06) -0.13 (0.06)	- -	- -
NAO_{AO}	- -	-0.23 (0.15) -0.26 (0.15)	- -
SOI	- -	- -	-0.26 (0.16) -0.26 (0.16)
SST_{Atl}	- -	- -	- -
SST_{Trop}	-1.25 (0.32) -1.13 (0.26)	- -	- -
Corrected	μ	σ	ν
Intercept	-0.82 (0.06) -0.80 (0.06)	2.59 (0.14) 2.50 (0.13)	-1.65 (0.25) -1.65 (0.25)
NAO_{MJ}	-0.18 (0.06) -0.14 (0.05)	0.23 (0.14) -	- -
NAO_{AO}	-0.12 (0.07) -0.09 (0.07)	- -0.24 (0.16)	- -
SOI	- -	- -	-0.26 (0.16) -0.26 (0.16)
SST_{Atl}	- -	- -0.62 (0.36)	- -
SST_{Trop}	-0.59 (0.31) -0.65 (0.24)	- -	- -